Multidimensional Poverty Dynamics in Ethiopia: How do they differ from Consumption-based Poverty Dynamics?[1]

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Abstract

Poverty can take many different forms, ranging widely over dimensions both monetary, such as consumption or income, and nonmonetary, such as health and education. One large class of nonmonetary measures of poverty is the multidimensional poverty index (MPI); recent studies document that people identified as poor in one dimension are often different from those who found to be poor in another dimension. This paper extends the literature by examining whether MDP dynamics are similar to the dynamics of a related consumption-based measure of poverty. Using two waves of Ethiopian panel data (2011-12 and 2013-14) we estimate poverty based on a monetary value of real consumption and a nonmonetary weighted deprivation index (our underlying measure of MDP). Similar to studies for other countries, we find that the two estimates of poverty identify significantly different groups of Ethiopians as poor. A key contribution of this paper is the finding that changes in consumption are largely independent of changes in multidimensional wellbeing: Awareness that an individual's wellbeing improved over time as measured by improvements in the weighted deprivation index provides no information about whether his or her wellbeing has improved where consumption is concerned.

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1. Introduction

Poverty is typically measured by estimating whether an individual has enough income, or consumes enough, to surpass some social definition of basic needs. This approach allows for a measure that can reflect many dimensions of wellbeing, such as consumption of food, shelter, transportation, and many other elements; it also can rely on market-determined prices to provide socially determined weights for each element. The appeal is in the simplicity of relying on economic interactions to provide assessments of the relative value of many different dimensions of wellbeing. One concern with this approach, however, is that there are nonmonetary dimensions of wellbeing that are excluded from the measures because there are no prices for them, possibly resulting in badly informed poverty policy discussions.

Alkire and Santos (2014) and Morrell (2011) both suggest that poverty is often a product of factors extending beyond income or consumption and that measuring it requires consideration of numerous elements and understanding how they interact over time. Hulme and Shepherd (2003) note that measures of poverty that focus on nonmonetary dimensions of wellbeing can serve as an important complement to monetary-based measures to paint a more complete picture of longer-term poverty and the experience of poverty.

Recognizing the shortcomings of monetary approaches to measuring poverty, and the complexity of multidimensionality, Alkire and Foster (2011) developed the now widely used Oxford Poverty and Human Development Initiative (OPHI) Multidimensional Poverty Index (MPI), along with the corresponding weighted deprivation index *(k)* and headcount indicator of multidimensional poverty (MDP).*K* takes into account three dimensions of wellbeing—health, education, and living standards—with each dimension contributing an equal share to the index. Selection of these dimensions and the corresponding indicators of deprivation is primarily driven by the quality of the data available, the context of the population of interest, and the research question (Alkire and Santos, 2010).

Alkire *et al*. (2014) also noted that consumption- and income-based poverty data are usually available only at intervals of three to ten years, limiting the ability to regularly track progress and make time-sensitive policy recommendations. In contrast, using MDP allows for flexibility in deciding which dimensions and indicators to include, how to establish thresholds for these indicators, and how relatively to weigh each factor of input. This leeway is particularly beneficial given the data constraints in developing countries. While absolute estimates of monetary poverty typically require expansive and detailed income or consumption datasets that meet specific international standards, MDP can be constructed using a variety of sources of data, including Demographic and Health Surveys (DHS) and Living Standards Measurement Surveys (LSMS).

In addition to divergences in the construction of consumption- or income-based poverty and of MDP, comparative studies reveal that the two measures may not necessarily be correlated. Bourguignon et al. (2010) and Alkire *et al.* (2014) concluded that positive income trends do not always represent improvements in non income deprivations. Comparing economic growth (GDP) in India and Bangladesh between 1990 and 2011, Dreze and Sen (2013) found that India's dominating GDP growth was dwarfed by Bangladesh's progress in improving under-5mortality rates, maternal mortality, immunization coverage, and female literacy. Examining cross-country data for 1990 to 2008, Bourguignon *et al.* (2008, 2010) found no significant correlation between non income MDGs and economic growth. Further, few studies have estimated MDP and consumption-based poverty from the same data. Klasen (2000) did so using a nationally representative dataset for South Africa and identified minimal overlap (2.9 percent) between the severely income-poor and the severely multiply-deprived; more recently, estimates of both measures of poverty were released by the Government of Bhutan using Bhutan's Living Standard Survey 2012 (Royal Government of Bhutan, 2014). For developed countries, Nolan and Whelan (2011) in their study of 26 European countries did not find any in which more than 50 percent of individuals experienced poverty in income *and* material deprivation indicators. Finally, in an analysis of 22 developing countries, Alkire and Roche (2013) found that only two countries exhibited statistically similar trends over time for both income-based and multidimensional poverty reduction.

Progress in reducing poverty is typically assessed by comparing cross-sectional trends over time. This method provides valuable information about changes in poverty among the population as a whole and helps us understand the risk factors for poverty at a given point in time, but it does not provide insight into the dynamics of poverty, such as identifying what characteristics determine whether a household transitions from poor to nonpoor and vice versa. However, panel data, which follow the same individuals or households over time, make it possible to capture more refined changes in poverty and thus assess poverty dynamics. Panels make it possible to look at the likelihood of moving in and out of poverty and to identify determinants of chronic vs. transient poverty. The latter is a crucial distinction; while chronic poverty may be more responsive to asset allocation and an increase in physical capital infrastructure, transient poverty typically requires safety nets or cash transfer programs (Baulch and Hoddinott, 2000; World Bank, 2001).

The literature on poverty dynamics is extensive, but the majority of the studies draw conclusions only about the dynamics of income- or consumption-based poverty (see Bane and Ellwood, 1986; Barrett, 2005; and Woolard and Klasen, 2005 for a few examples). However, there is a growing, though still relatively young, literature on the dynamics of MDP (Apablaza and Yalonetzky, 2013).These studies suggest that changes in MDP take place much more slowly than in monetary-based poverty. Since being considered multidimensionally nonpoor necessitates accumulation of assets and increased investment in health and education, households are not likely to move in and out of MDP rapidly or repeatedly. For this reason, it is widely agreed that MDP is more indicative of long-term poverty. A household’s consumption- or income-based poverty status, on the other hand, can change rapidly (Alkire and Roche, 2013) with a sudden increase in income (moving the household out of a poor state) or an idiosyncratic shock (moving the household into a poor state). Finally, while some studies (as noted above) compare *trends* in consumption-based poverty and MDP, very few have looked at the extent to which these two indicators co-move at the household level.

The Ethiopia Socioeconomic Survey (ESS)[4] dataset used in this analysis is unique in two ways: (1) It ambitiously follows a panel sample of Ethiopian households that is representative of all rural and small-town households, allowing for analysis of MDP trends and dynamics over time. (2) In addition to collecting data on well being that can be used as inputs for MDP, the ESS has detailed consumption and income modules which enable us to compare trends and dynamics of poverty using both traditional and multidimensional measures. Our findings suggest there have been mild declines in MDP among rural and small-town Ethiopians. Of nine deprivations studied, lack of access to an improved water source saw the largest decline, falling about11.1 percent between 2012 and 2014.Panel data analysis reveals that nearly 82percent of households were poor in both waves (were chronically multidimensionally poor), 4 percent fell into poverty between the waves, 8 percent escaped poverty, and 6 percent stayed nonpoor.

We also find that the bottom 30 percent of the distributions of *k* and consumption per adult equivalent contain minimal overlap; among those in the bottom 30 percent of the distribution in either dimension, only 35 percent fall in the bottom of the other dimension. We then contribute to the literature on the dynamics of wellbeing by finding considerably different patterns of mobility for individuals when *k* is compared with consumption; an individual's change in *k* thus provides no insight into his or her change in consumption, and vice versa. We also find evidence suggesting that adverse shocks are picked up by nonmonetary but not monetary measures of poverty, which further supports the notion that policymakers tracking changes in wellbeing would be wisest to apply both monetary and nonmonetary measures.

[4] The ESS is a collaborative project of the Central Statistics Agency of Ethiopia (CSA) and the World Bank Living Standards Measurement Study- Integrated Surveys of Agriculture (LSMS-ISA) project that collects multitopic panel data at the household level.

In what follows, section 2 describes the data and construction of the multidimensional estimates of poverty. Section 3 presents cross-sectional trends and panel dynamics for MDP. Section 4 explores differences between MDP and consumption-based poverty, as well as between the underlying indicators, in both the cross-section and dynamically. Section 5 discusses the findings, and section 6 concludes.

2. Study Setting and Data

2.1 Study Setting

MDP in Ethiopia is quite high, especially compared to other countries in the region (Alkire and Roche, 2013). In 2011, according to OPHI estimates derived from DHS data, 87.3 percent of Ethiopians were multidimensionally poor[5], making it the second poorest country in the world in this dimension (OPHI, 2013). Between 2005 and 2011, MDP declined only 2.2 percentage points (pp); in the same period, income poverty declined more than twice as fast (Alkire and Roche, 2013). Yet using the national monetary poverty line, in 2011 only 29.6 percent of the Ethiopian population was considered poor (World Bank, 2015).

Dercon and Krishnan (2000) looked at the dynamics of consumption-based poverty in rural Ethiopia using data from three points in time, each six months apart, and found that 30 percent of rural Ethiopian households were 'sometimes poor' and 24.8 percent were 'always poor'. In comparing a consumption-centric poverty measure to MDP, Brück and Kebede (2013) hypothesized that in rural Ethiopia short-term shocks impact consumption poverty and simultaneous long-term shocks affect MDP. Theyfound that drought plays a role only in consumption poverty. Furthermore, they found that a large segement of households are either exclusively MDP or consumption-poor and thatsome MDP households are among those in the top quintile of consumption.

[5] OPHI defines MDP at $k >= 0.33$.

2.2 Data

We analyzed data from two waves of the ESS, which began as the Ethiopia Rural Socioeconomic Survey (ERSS) in 2011 (ESS1). The first wave of data collection covered only rural and small-town areas. In 2013, when a second wave of the survey was administered, the sample was expanded to urban areas (ESS2). Our analysis was restricted to the panel sample, which is nationally representative of all rural and small-town areas in Ethiopia. For the panel sample, the survey was conducted in a series of three visits: the post-planting questionnaire was administered between September and October of 2011 (ESS1) and 2013 (ESS2); the livestock questionnaire in November of 2011 (ESS1) and 2013 (ESS3); and the household, community, and post-harvest questionnaires between January and April of 2012 (ESS1) and 2014 (ESS2).

The ESS used a stratified, two-stage sampling scheme[6]. The regions of Ethiopia served as the strata, from which enumeration areas (EAs) were selected proportionally based on the regional population[7]. A total of 290 EAs were selected from rural areas and 43 from small towns; 12 households were then chosen from each EA. The first wave had an extremely low nonresponse rate of 0.7%; the final interviewed sample was 3,969 households. Tracking between ESS1 and ESS2 was done at the household level and at 4.9 percent the attrition rate was also very low, producing a sample of 3,776 households which were surveyed in both waves. To maintain the same balanced panel sample for all analyses, we further restricted the final analytical sample by excluding households for which information was missing on any of the nine deprivations or on real consumption per adult equivalent. Restricting households with such item nonresponses resulted in a loss of 15 percent of the sample, for a final

[6] For detailed information on the sampling design, see the Basic Information Document at http://go.worldbank.org/ZK2ZDZYDD0.

[7] Due to sample size constraints, the data are only regionally representative for the most populous regions: Amhara, Oromiya, SNNP, and Tigray.

balanced sample of 3,197 households[8].

2.3 Weighted Deprivation Index and MDP

We used the OPHI methodology as a guide in creating our weighted deprivation index; because the ESS is an extensive survey, we were able to include in it nearly all OPHI-defined deprivations. However, a few modifications were needed because we were using only one data source (of course, the gain is that we were able to use panel data to analyze the dynamics of MDP).Figure 1illustrates where our list of deprivations diverges from those in the OPHI index[9].In line with the OPHI methodology, we incorporate three dimensions of wellbeing— education, health, and living standards—with each dimension weighted to represent one-third of the index. Individual indicators are weighted equally within a given dimension (Figure 1).

Deprivations from OPHI's methodology incorporated into our index were[10]: **1a.** At least one child aged 7-15 years in the household is not attending school. **1b.** No one in the household has at least six years of education. **2b.** Household does not have access to an improved water source. **2c.** Household does not have access to improved sanitation. **3a.** Household does not have access to electricity. **3b.** Household does not have a finished floor. **3c.** Household does not use solid cooking fuel. **3d.** Household does not have a

[8] A household is in our final balanced sample only if it is in both waves and not missing any variables of interest. However, this does not guarantee the composition of the households is the same in both waves. A panel household may, for example, have four members in wave 1 and five in wave 2.

[9]Dimensions and indicators are often selected based on data constraints as well as alignment with researcher aspirations. While Alkire and Santos (2010) used child mortality and nutrition as health indicators, due to data availability constraints Brück and Kebede (2013) used child mortality and adult morbidity, which suggests indicating the flexibility of MDP measures. Brück and Kebede also added access to water as their study's living standard indicator in line with the Millennium Development Goals. Alkire and Santos also used nested weights in which dimensions and the indicators within them are weighed equally. By calculating significance probabilities, Brück and Kebede found indicators within dimensions to be highly dependent on one another, which suggested their appropriate categorization.

[10] Indicator numbers correspond to those in Figure 1.

radio, television, or phone, or the household lacks a transportation asset as well as land, livestock, or a refrigerator. In contrast to OPHI's *k*, our index does not include an indicator of recent cases of mortality within the household because this information was only collected in wave 2 of the ESS and thus cannot be assessed in the panel dimension.

The other primary difference between the two indices is found in deprivation 2a: in the OPHI methodology, this indicator takes into account both child and adult malnutrition, whereas our indicator provides information only about child malnutrition. Thus, deprivation 2a in our index is defined as the household having at least one stunted child aged 6-59 months.[11]

[11]Households ineligible for a certain deprivation are automatically considered 'not deprived'. For example, for deprivation 2a, households with no children aged 6-59 months are not deprived.

Figure 1: Constructing *k*, divergences from OPHI

Dimension	OPHI index	Our index	Criteria for deprivation
1. Education (1/3)	Years of schooling (1/6)	Years of schooling (1/6)	1a. At least one child aged 7-15 years is not attending school
	School attendance (1/6)	School attendance (1/6)	1b. No one in the household has at least 6 years of education
2. Health (1/3)	Child mortality (1/6)	Nutrition (1/9)	2a. At least one 6-59-month-old child in the household is stunted
	Nutrition (1/6)	Water (1/9)	2b. Household does not have access to an improved water source
		Sanitation (1/9)	2c. Household does not have access to an improved sanitation facility
3. Living Standards (1/3)	Electricity (1/18)	Electricity (1/12)	3a. Household does not have access to electricity
	Sanitation (1/18)		
	Water (1/18)	Floor (1/12)	3b. Household does not have a finished floor
	Floor (1/18)		
	Cooking fuel (1/18)	Cooking fuel 1/12)	3c. Household does not use solid cooking fuel (uses wood, charcoal, leaves, or manure)
	Assets (1/18)		

To classify a household as poor or nonpoor, a minimum number of weighted dimensions are established and only those who are deprived in dimensions exceeding this value are considered poor (Alkire and Foster, 2011). OPHI traditionally uses a cutoff of k>=0.33 to define the poverty threshold. We analyze results separately, using two different cutoff points:(1) We use the standard cutoff of k>=0.33 to make results comparable with external estimates of MDP. (2)We identify the value of k in each wave such that the proportion of individuals experiencing MDP matches the proportion facing relative consumption-based poverty (approximately 30 percent in rural and small-town areas).[12] By allowing k to change each year, this estimate (hereafter referred to as multidimensional-equivalent poverty [MDEP])can similarly be thought of as a relative nonmonetary estimate of poverty.

3 Results

3.1 Trends in MDP

The ESS data suggest that between 2012 and 2014MDPdeclined in rural and small-town areas of Ethiopia from 90 to 86 percent. Table 1 highlights trends for each deprivation, elucidating which dimensions are likely to have been responsible for the4pp decrease in MDP. Deprivation 2b, having no access to an improved source of drinking water[13], saw the largest decline, from 47.7 percent to 36.5 percent. This improvement is in line with the progress observed from 2000 to 2011, when the proportion of those without access to improved water fell from 82 to 59 percent (Ambel *et al.*, 2015)[14]. Mild improvements are also observed for deprivations 1b and 3d, suggesting that, on average, households are becoming more educated and are acquiring more communication, transportation, and other assets. In both years the prevalence

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[12] This is derived from the official rural prevalence of poverty in 2010/11 reported by Ethiopia's Ministry of Finance and Economic Development.

[13] Improved water sources as defined by WHO (2006) consist of water piped into a dwelling, water piped into a yard or plot, a public tap or standpipe, a tubewell or borehole, a protected dug well, a protected spring, bottled water, or rainwater.

[14] Note that the 2000-2011 estimates are derived from a different data source, the Welfare Monitoring Survey (WMS), a nationally representative survey carried out in 2000, 2005, and 2011. Nonetheless, both our results and those of Ambel, Mehta, and Yigezu (2015) highlight similar patterns of change in access to improved water.

of deprivations in household use of solid cooking fuel and ownership of a finished floor hovered near 97 percent. Finally, we do not observe statistically significant worsening in any single deprivation.

Table 1: Trends in deprivations underlying *k*

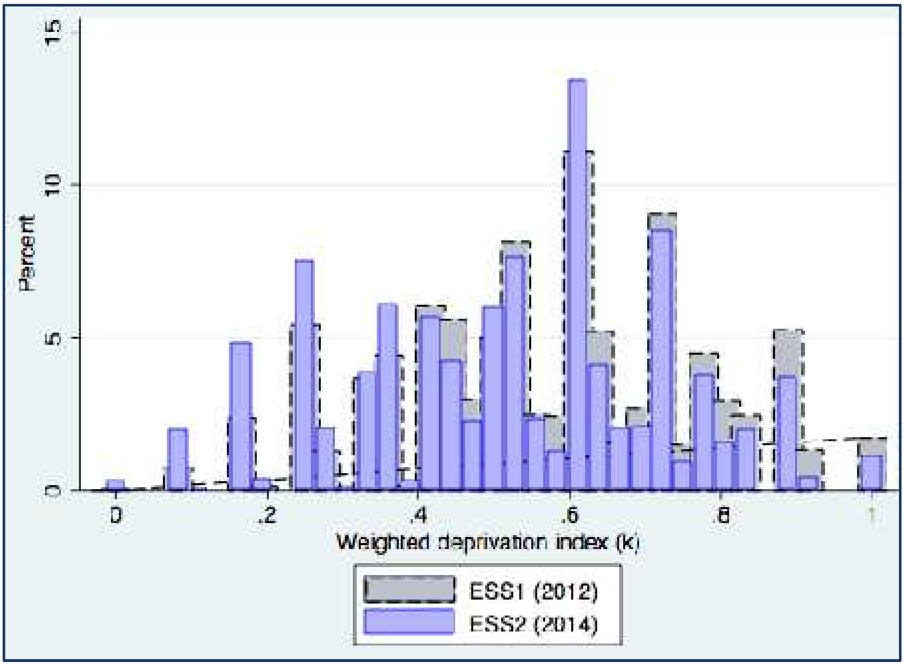
	2012 (SEs)	2014 (SEs)	2014-2012
1a. At least 1 child aged 7-15 not in school	0.272	0.277	0.005
	(0.016)	(0.014)	
1b. No one in household has at > 6 years of education	0.663	0.601	-0.062***
	(0.017)	(0.018)	
2a. A child aged 6-59 months is stunted	0.244	0.213	-0.031**
	(0.013)	(0.012)	
2b. No access to improved drinking water	0.476	0.365	-0.111***
	(0.031)	(0.028)	
2c. No access to improved sanitation	0.394	0.407	0.013
	(0.025)	(0.024)	
3a. No access to electricity	0.873	0.855	-0.018**
	(0.016)	(0.017)	
3b. Household does not use solid cooking fuel	0.972	0.984	0.012
	(0.013)	(0.005)	
3c. Household does not have a finished floor	0.961	0.958	-0.003
	(0.006)	(0.006)	
3d. Household missing community or mobility/livelihood asset	0.612	0.546	-0.066***
	(0.019)	(0.018)	

Note: Difference is significant at *p<0.1; **p<0.05; ***p<0.01. Observations are weighted to make results representative of all rural and small-town individuals in Ethiopia. Balanced panel sample size was 3,197 households in each wave. Standard errors are adjusted for stratification and clustering.

After constructing the weighted sum of all nine deprivations, *k*, we compare shifts in its distribution between waves 1 and 2. We observe mild improvements in the distribution; with mass shifting to the left in 2014 (see

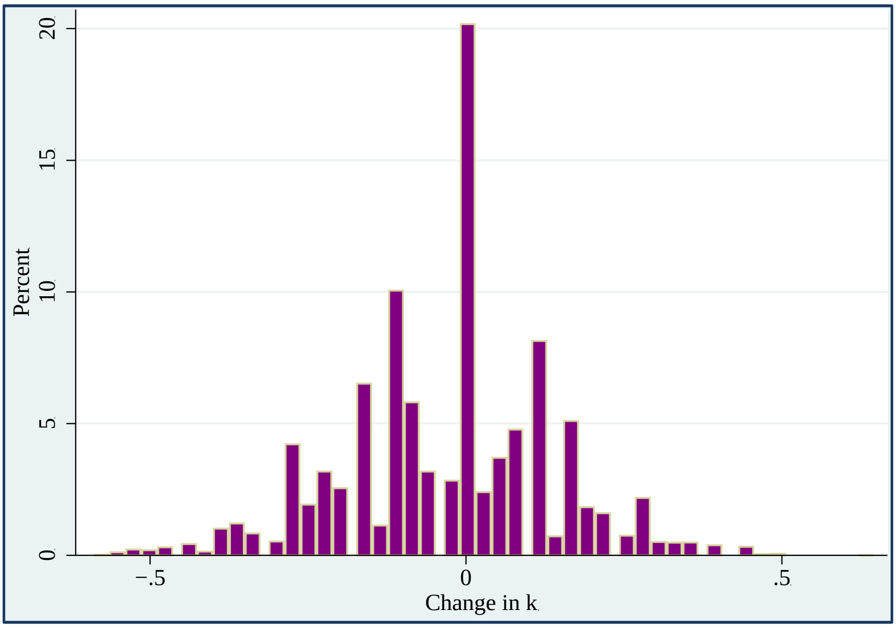
Figure 2). Furthermore, we observe at least some improvement across the entire distribution; the proportion of individuals with extremely high *k* values also decreases slightly between 2012 and 2014, signaling some progress among those suffering from extreme MDP. However, the improvements observed on the left side of the distribution (where individuals exhibit fewer deprivations) are greater in magnitude than those observed among the extremely poor.

Figure 2: Distribution of deprivation (*k*), 2012 and 2014



While Figure 2 tells us about the overall changes in *k* at the national level, it provides no insight into the average magnitude of change experienced at the individual level. However, using a panel dataset, we can assess the average size of the changes individuals experienced in multidimensional wellbeing between waves 1 and 2.Figure 3 presents the distribution of change in *k*. As expected given the modest shifts to the left, over the same period we find that more individuals enjoyed a decline in deprivations (47 percent) than accumulated more deprivations (33 percent). Nonetheless, we still see a considerable mass centered around zero. In wave 2 nearly 38 percent of the population deviated less than 0.1 from their wave 1 *k* value, and 20 percent experienced no change in their deprivation index.

Figure 3: Distribution of change in deprivation (*k*), 2012-2014



3.2 MDP Dynamics

Table 2 portrays the dynamics of MDP in rural and small-town Ethiopia between 2012 and 2014. Some 82 percent of households are chronically poor, meaning that in both waves their deprivation index was at least *k*=0.33.Movement in and out of MDP was minimal—only 11 percent of households experienced a transition; however, nearly twice as many households exited than entered poverty (7.54 vs. 3.69 percent).Perhaps not surprisingly, these dynamics vary significantly by rural and small-town area and between regions. While 86 percent of households in rural areas are chronically multidimensionally poor, this is a persistent burden for only 38 percent of small-town households. Furthermore, the share of small-town households exiting poverty between 2012 and 2014 is more than double the proportion doing so in rural areas (16.71 vs. 6.88 percent).

Amhara exhibits the highest burden of chronic poverty: more than88 percent of its households were poor in both waves. SNNP, with only 78 percent of households in chronic poverty, also has the highest relative share, 9.67 percent, of households that were nonpoor in both waves. The largest relative decline in poverty between waves 1 and 2 is observed in the 'other regions' category, where 10 percent of households improved their multidimensional wellbeing and exited poverty. In Amhara only 6 percent of households exited poverty.

Table 2: MDP dynamics, *k*=0.33

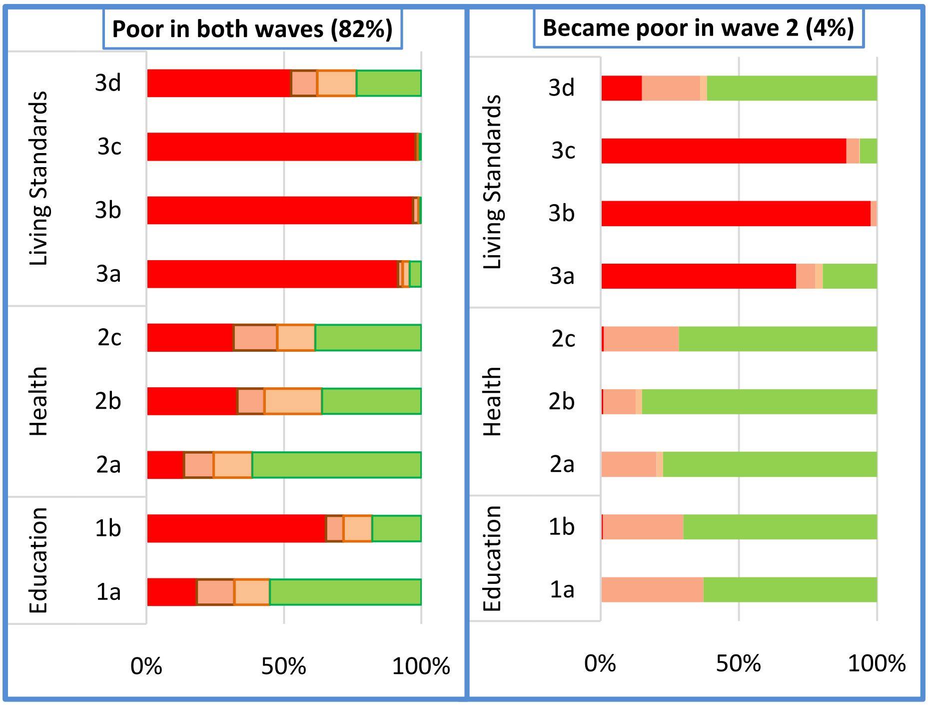
	Poor in both waves	Become poor in wave 2	No longer poor in wave 2	Not poor in either wave	Sample size (households)
Total	82.47	3.69	7.54	6.30	3,197
Rural	85.65	3.38	6.88	4.09	2,799
Small town	38.44	7.99	16.71	36.86	398
Amhara	88.47	2.12	5.63	5.78	715
Oromiya	82.67	4.62	8.10	4.61	636
SNNP	78.30	3.99	8.05	9.67	848
Tigray	81.32	4.24	8.30	6.13	337
All other regions	80.77	2.45	9.52	7.25	661

Note: Observations are weighted to make results representative of all rural and small-town individuals in Ethiopia. Balanced panel sample size consists of 3,197 households.

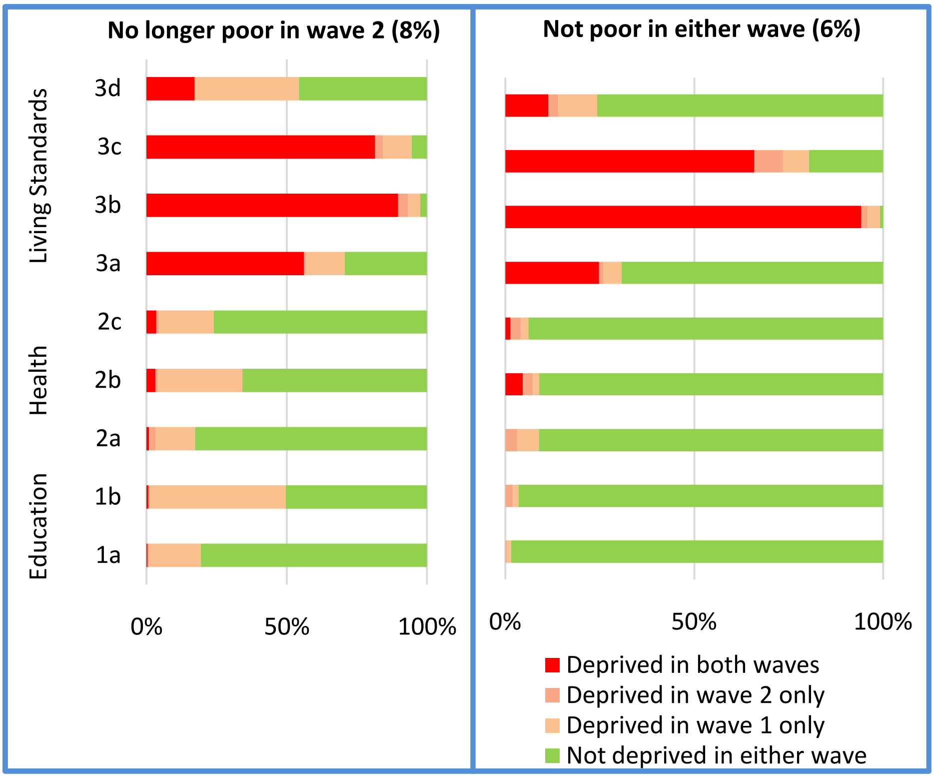
Next, we analyze the dynamics of each individual deprivation separately, according to the category of a household's poverty dynamic. This helps us assess the extent to which households within a given category look similar in terms of specific deprivations. This analysis can be particularly insightful for the two transitioning groups of households. For example, do nearly all households moving out of an MDP state between waves see an improvement in a particular deprivation? Similarly, what new deprivation may be causing a household that was previously nonpoor to enter a poor state?

Regarding the latter question, we find that households moving into poverty in wave 2 are significantly more likely than any other group to become deprived in indicators 1a, 1b, and 3d, meaning they are most likely falling into MDP due to a decline in their education levels, participation, or living standard assets. Conversely, households that exit poverty are most likely to experience an improvement in indicators 1b and 3d, as well as in 2b. Thus, a household's escape from poverty is most likely driven by asset acquisition, increased investment in duration of education, and new access to an improved water source. We also find that housing-related deprivations (3a, 3b, and 3c) represent the most prevalent chronic deficits for all four poverty dynamic groups and are virtually universal among the chronically poor; for example, in both waves 97.9 percent of chronically poor households do not use solid cooking fuel.[15]

Figure 4: Dynamics of deprivations, by poverty dynamics category



[15] Ballon and Apablaza (2012) note similarly high levels of housing-related deprivations among those chronically suffering MDP in Indonesia.



4 MDP and Consumption-Based Poverty

4.1 Contrasting MDP and Consumption-based Poverty in the Cross-section

In the previous section, we used an MDP cutoff of k>=0.33to mimic the standard cutoff approach. To better assess the overlap between multidimensional and consumption-based poverty, which is significantly lower than MDP defined using a k>=0.33 cutoff, we look at a new estimate of MDP that uses a more severe threshold. We identify the k cutoff such that MDP equals consumption-based poverty in wave 1 (30 percent among rural and small-town households), and relative consumption-based poverty in wave 2 (also the bottom 30 percent among rural and small-town households). The corresponding weighted deprivation values are k>=0.72 in wave 1 and k>=0.67 in wave 2; households with a k value above or equal to

0.72 in wave 1 (or above or equal to 0.67 in wave 2) are considered to be MDEP[16]. In this section, we explore the extent to which these two estimates of poverty identify the same individuals as poor, as well as compare overlap in the two underlying indicators, consumption and *k*.

Tables 3a and 3b depict the overlap and mismatch between MDEP and consumption-based poverty estimates in 2012 and 2014.Dual poverty, defined as falling in the bottom 30 percent of the distributions of both real annual consumption per adult equivalent and *k*, was 12 percent among rural and small-town households in both years. Oromiya has the lowest prevalence of dual poverty at 8 percent in both 2012 and 2014.Nationally, more than half of individuals considered poor in one dimension are *not* considered poor in the other. This dissonance can have important implications for policy development targeted towards the 'poor'.

Furthermore, those that are MDEP but not monetarily poor as compared to the reverse are not consistent across regions. For example, in both years, in SNNP the relative burden of consumption-based-only poverty is greater than that of MDE-only poverty. In Oromiya, the opposite is true; the prevalence of MDEP-only is nearly double that of consumption-based-only poverty. The minimal overlap observed between the two estimates of poverty parallels findings from similar studies in other countries.[17]

[16] See Appendix Table A for the MDEP dynamics (similar to Table 3).

[17] See presentations from the OPHI workshop, "Dynamic Comparison between Multidimensional Poverty and Monetary Poverty" at http://www.ophi.org.uk/workshop-on-monetary-and-multidimensional-poverty-measures/.

Table 3a: Overlap of consumption-based poverty and MDEP, 2012

MDEP	Poor	Poor	Nonpoor	Nonpoor	Overlap
Consumption-based	**Poor**	**Nonpoor**	**Poor**	**Nonpoor**	
National (rural and small town)	0.12	0.16	0.18	0.54	0.66
Rural	0.13	0.17	0.18	0.53	0.66
Small town	0.03	0.01	0.17	0.78	0.81
Domains of analysis					
Amhara	0.18	0.18	0.25	0.39	0.57
Oromiya	0.08	0.17	0.11	0.64	0.72
SNNP	0.12	0.11	0.21	0.55	0.67
Tigray	0.11	0.17	0.15	0.57	0.68
All other regions	0.12	0.20	0.16	0.52	0.64

Note: Observations are weighted to make results representative of all rural and small-town individuals in Ethiopia. Balanced panel sample consists of 3,197 households.

Table 3b: Overlap of consumption-based poverty and MDEP, 2014

MDEP	Poor	Poor	Nonpoor	Nonpoor	Overlap
Consumption-based	**Poor**	**Nonpoor**	**Poor**	**Nonpoor**	
National	0.12	0.16	0.18	0.53	0.65
Rural	0.13	0.17	0.18	0.52	0.65
Small town	0.02	0.04	0.16	0.78	0.80
Domains of analysis					
Amhara	0.16	0.18	0.24	0.42	0.58
Oromiya	0.08	0.17	0.13	0.61	0.69
SNNP	0.16	0.10	0.22	0.53	0.69
Tigray	0.09	0.16	0.14	0.61	0.70
All other regions	0.12	0.20	0.21	0.47	0.59

Note: Observations are weighted to make results representative of all rural and small town individuals in Ethiopia. Balanced panel sample consists of 3,197 households.

Tables 4a and 4b demonstrate where individuals fall on the intersection of the distributions of annual consumption per adult equivalent and *k*. In 2012, only about 27 percent of rural and small-town Ethiopians fell into the same quintile of both distributions; 34 percent of individuals were one quintile apart when the two indicators were compared; and 39 percent were two or more quintiles apart. The pattern in 2014 was similar. This supports our assertion that whether we use a monetary or nonmonetary measure of poverty makes a difference in who will be identified as poor. In fact, 73 percent of individuals would be placed in a different quintile depending on whether or not wellbeing was being defined by consumption or by deprivations in nonmonetary dimensions.

Table 4a: Cross-tabulation of consumption and k quintiles, 2012

Consumption quintiles	Quintiles of k (weighted deprivation index)				
	Poorest	**2nd**	**3rd**	**4th**	**Wealthiest**
Poorest	5.98	4.34	3.38	3.29	2.99
2nd	5.06	4.57	2.74	3.76	3.74
3rd	3.63	2.86	3.95	4.92	4.26
4th	2.96	3.82	3.12	4.47	5.93
Wealthiest	1.76	2.35	3.18	5.3	7.63

Table 4b: Cross-tabulation of consumption and k quintiles, 2014

Consumption quintiles	Quintiles of k (weighted deprivation index)				
	Poorest	**2nd**	**3rd**	**4th**	**Wealthiest**
Poorest	5.46	3.87	5.48	3.5	2.48
2nd	5.09	3.17	4.37	3.65	3.86
3rd	3.08	3.41	5.01	4.77	4.5
4th	2.02	3.04	4.66	3.8	5.78
Wealthiest	1.14	2.17	4.33	3.78	7.57

Note: Green cells represent individuals who fall in the same quintile whether the underlying variable is *k* or consumption; yellow individuals classified as one quintile apart; and red individuals who are two or more quintiles apart depending on the underlying variable.

4.2 MDEP and Consumption-based Poverty Dynamics Compared

In the previous subsection, we discovered significant differences in the distributions and corresponding poverty estimates between measures of MDEP and a relative measure of monetary wellbeing (for both measures, we define as poor an individual who falls in the bottom 30 percent of the distribution). This finding underscores the fact that numerous factors must be considered when deciding which measure to use for calculating poverty or identifying particularly vulnerable groups. In this subsection, we compare the dynamics of multidimensional and monetary wellbeing between the two waves and find significant differences in panel dynamics between the two measures, as well as evidence suggesting there is little to signal changes in *k* and changes in consumption.

Figure 5 contrasts the dynamics of MDEP and relative consumption-based poverty. Depictions of chronicity differ depending on the underlying measure. In contrast to the 17 percent of rural and small-town Ethiopians who face chronic MDEP, using traditional consumption-based estimates only 14 percent are identified as chronically poor. We also find that consumption-based poverty shifts more substantially, with nearly 31 percent moving in or out of poverty between 2012 and 2014; only 26 percent of households transitioned between multidimensionally poor and nonpoor states.

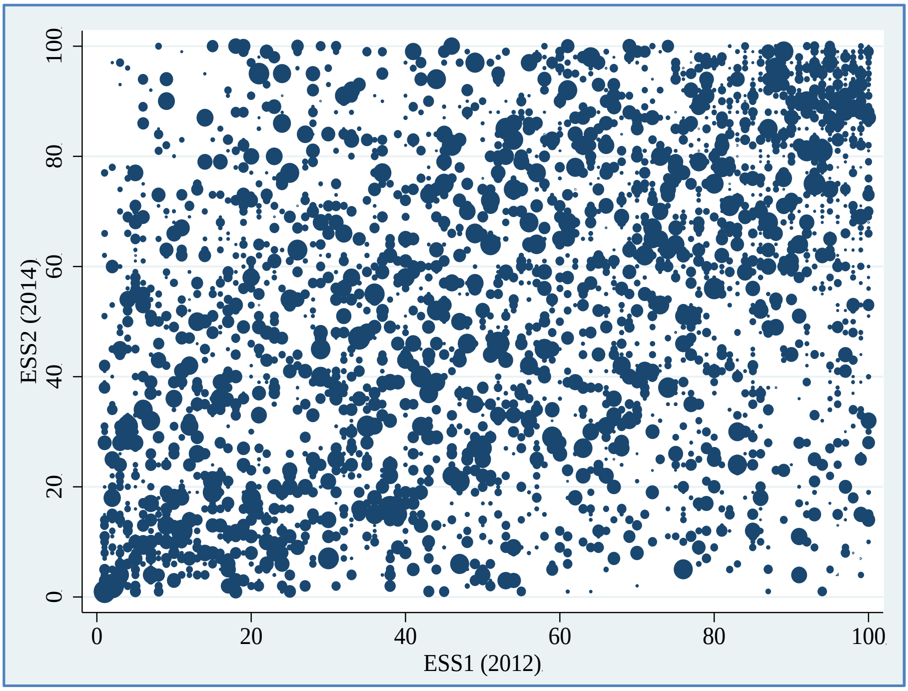
Figure 5: Dynamics of MDEP and relative consumption-based poverty, Percent

		MDEP		Consumption-based poverty	
		Wave 2		Wave 2	
		Poor	Nonpoor	Poor	Nonpoor
Wave 1	Poor	16.6	12.4	14.4	14.4
	Not poor	11.6	59.4	16.2	55.0

Note: Dark red cells represent chronically poor individuals, light red those who fell into poverty between waves 1 and 2, light green those who have exited poverty, and dark green those were not poor in either wave.

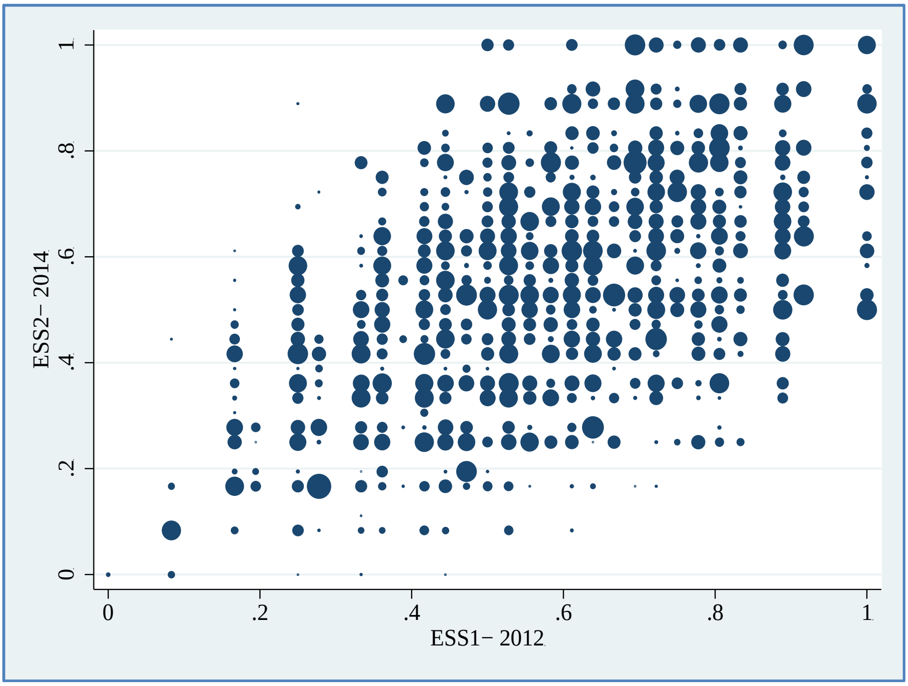
The marked difference in movement over time between *k* and annual consumption per adult equivalent is demonstrated in Figures 6 and 7. The scatter plot of annual consumption per adult equivalent (expressed in percentiles) between 2012 and 2014 is widely dispersed. Though households are more densely concentrated along the 45-degree line of equality, there is still significant variation. This suggests that it is relatively easy for a household to move substantially up or down the consumption gradient over a short period; a sizable proportion of households in the top quintile of consumption in 2012 fall into the bottom quintile in 2014, and vice versa. In comparison, the scatter plot of *k* is significantly more concentrated at the line of equality. There are effectively no households with $k<0.20$ in 2012 but $k>0.80$ in 2014, or vice versa.

Figure 6: Annual consumption per adult equivalent, 2012 and 2014, percent



These findings suggest that real annual consumption per adult equivalent, the underlying variable for consumption-based poverty, is significantly more volatile than*k*, the input variable for MDEP, and that the *k* value in wave 1 is more predictive of the *k* value in wave 2. In fact, while the *k* values of the two waves have a statistically significant correlation coefficient of 0.662, consumption in wave 2 is correlated only 18 percent with wave 1 consumption. Put another way, having information about an individual's *k* value in wave 1 helps predict the *k* value in wave 2, but knowing an individual's consumption in period 1 does not help to accurately predict consumption in wave 2.

Figure 7: Weighted deprivations index (*k*), 2012 and 2014



Furthermore, knowing what happens to an individual's *k* between waves does not provide any useful information about what happens to that individual's consumption, and vice versa. Approximately 59 percent of individuals whose *k* worsened between waves also experienced a decline in consumption; the other 41 percent saw their consumption improve (see Table 5a).Similarly, for nearly 53 percent of individuals who improved in *k* their consumption actually worsened. In fact, using the Pearson's chi-squared test of independence, we fail to reject the null hypothesis that the two distributions are independent (p=0.267).

Table 5a: Contrasting changes in *k* and changes in consumption

Real consumption per adult equivalent	***K***			***Total***
	Worsened	**Stayed the same**	**Improved**	
Worsened	0.191	0.112	0.297	*0.552*
Improved	0.139	0.091	0.218	*0.448*
Total	*0.330*	*0.203*	*0.475*	*1.000*

Note: A Pearson's chi-squared test of independence fails at p=0.267 to reject the null hypothesis that the two variables are independent of each other. Observations are weighted to make results representative of all rural and small-town individuals in Ethiopia. The balanced panel sample covers 3,197 households.

However, if we aggregate information on *k* and consumption so that we are looking at changes over certain thresholds rather than just increases or decreases, we do observe some signaling between the two categorical distributions. Panel A in Table 5b demonstrates the contingency table for consumption-based poverty and MDP (defined as *k*>=0.33). Given the considerable mass centered in the middle (60.6 percent of individuals do not move past the threshold in either dimension), we find that there is some dependence between the two distributions. Using Pearson's chi-squared test of independence, we reject the null hypothesis that the two distributions are independent at p=0.003. An individual's movement in or out of MDP does provide some information content on that individual's movement in or out of consumption-based poverty. However, we find that this signal declines substantially if the *k* threshold is increased to match that for MDEP. Here (see Panel B in Table 5b), we reject the null hypothesis with only minimal confidence.

Table 5b: Contrasting changes in relative consumption-based poverty, MDP, and MDEP

Relative consumption-based poverty	Panel A -- MDP			*Total*
	Worsened	**Stayed the same**	**Improved**	
Worsened	0.002	0.153	0.007	*0.162*
Stayed the same	0.032	0.606	0.056	*0.694*
Improved	0.002	0.131	0.011	*0.144*
Total	*0.037*	*0.890*	*0.069*	*1.000*
	Panel B --MDEP			
Worsened	0.028	0.112	0.023	*0.162*
Stayed the same	0.073	0.536	0.085	*0.694*
Improved	0.016	0.113	0.016	*0.144*
Total	*0.116*	*0.760*	*0.124*	*1.000*

Note: A Pearson's chi-squared test of independence for Panel A fails, at p=0.003, to reject the null hypothesis that the two variables are independent of each other. For Panel B, at p=0.069 the test also fails to reject the null. Observations are weighted to make results representative of all rural and small-town individuals in Ethiopia. The balanced panel sample covers 3,197 households.

The findings presented in Tables 5a and 5b pose a dilemma for policymakers because consumption and *k* are two measures that should both be measuring wellbeing but they are not moving together. How should policymakers evaluate the content of these two measures, both of which are presumed to be measuring wellbeing? We explore this issue by examining how each of the measures is correlated with adverse shocks that should presumably be adversely affecting both measures. We find that shocks are driving movement as expected with MDEP but not with relative consumption-based poverty.

Table 6 presents mean values for having experienced various shocks between waves 1 and 2, according to an individual's poverty dynamic group as measured through monetary and nonmonetary dimensions. We also compare estimates between groups with the same baseline poverty status; for instance, among those who were nonpoor in 2012, we examine whether there are observed differences in experiencing a shock between waves for those that remained nonpoor vs. those who fell into poverty.

Table 6: Exposure to shocks across poverty dynamic categories, MDEP and consumption-based poverty

	Poor in both waves	Become poor in W2	No longer poor in W2	Not poor in either wave	Diff. for moving out of poverty	Diff. for moving into poverty
	(i)	(ii)	(iii)	(iv)	(i)-(iii)	(ii)-(iv)
MDEP						
Any shock in last 12 mos	0.46	0.46	0.40	0.32	0.063	0.148**
Food price shock	0.15	0.22	0.15	0.09	-0.001	0.130***
Natural disaster	0.20	0.13	0.14	0.10	0.055	0.027
Price of agric. input shock	0.09	0.18	0.11	0.08	-0.022	0.094**
Loss of livestock	0.06	0.05	0.06	0.03	0.003	0.023
Death/illness in household	0.13	0.10	0.12	0.11	0.012	-0.006
Relative consumption-based poverty						
Any shock in last 12 mos	0.37	0.39	0.34	0.37	0.030	0.022
Food price shock	0.16	0.17	0.10	0.11	0.060	0.064**
Natural disaster	0.17	0.12	0.14	0.11	0.027	0.009
Price of agric. input shock	0.07	0.10	0.07	0.11	-0.003	-0.010
Loss of livestock	0.02	0.07	0.04	0.04	-0.015	0.038
Death/illness in household	0.12	0.10	0.07	0.13	0.049	-0.023

Note: The values are mean values of the row labels within each poverty dynamic category. For example, the top left cell can be translated as '46 percent of chronically MDEP households have experienced a shock between waves 1 and 2'. MDEP is defined as having k>=0.72 in wave 1 and k>=0.67 in wave2. Observations are weighted to make results representative of all rural and small-town individuals in Ethiopia. Differences and F-tests are significant at *p<0.1; **p<0.05; ***p<0.01. The balanced panel sample covers 3,197 households in each wave.

Among households that were not MDE poor in 2012, those that fell into poverty were 15pp more likely to have experienced a shock between the two waves. This pattern is not observed when looking at movement across consumption-based poverty dynamics categories. Furthermore, MDEP appears to shift depending on whether the shocks were to food prices or agricultural input prices. Thus, from a policy standpoint MDEP has the desirable quality that it is correlated with something that can be expected to have adverse effects on wellbeing.[18]

Whether or not this finding is generalizable, we consider it a useful insight for Ethiopia.

5 Discussion

The evidence suggesting that shocks can drive changes in nonmonetary measures of poverty implies that *k* can be a useful indicator for monitoring reactions to adverse shocks. One possible explanation for why the consumption poverty measure does not seem to identify these same shocks as clearly is that consumption may contain more measurement error (as suggested by the evidence on the sensitivity of measured consumption to questionnaire design) than is found in *k*.

The susceptibility of income and consumption data to measurement error is widely recognized (see, e.g., Bound and Krueger, 1991; Pischke, 1995). Due to the time and financial burdens associated with diaries, ESS consumption data are collected using recall questionnaires. Sarkar (2012) suggests respondent recall error can contribute to mismeasurement in actual consumption. Furthermore, the length of the period recalled can affect a respondent's recall: Longer periods make it harder for the respondent to correctly remember consumption behaviors, but shorter periods may lead to magnification of recall bias, since reported consumption will have to be scaled up more to calculate annual consumption. The latter is particularly

[18] The Alkire-Foster method (2011) allows for significant flexibility in selecting components. The process of choosing deprivations for inclusion in the underlying index is arbitrary and largely dependent on data availability. Given the components selected for measuring MDP here, it is perhaps not surprising that changes in MDEP are correlated with exposure to certain shocks.

problematic for food consumption data which, typically and in the case of the ESS, are collected for the 7 days preceding the survey. In fact, Lanjouw and Lanjouw (1997) suggest that there can be considerable mismeasurement of food consumption and expenditure in household surveys.(For further evidence of the sensitivity of measured consumption to questionnaire design, see Jolliffe, 2001; Winter, 2003; Pradhan, 2009; Beegle *et al.* 2012; Browning *et al.* 2014; and Jolliffe *et al.*, 2014.)

Furthermore, consumption-based poverty estimates require numerous inputs in addition to household survey reports of consumption. These factors, among them spatial and temporal price indices, prices for nonpurchased goods, and equivalence scales, are vulnerable to their own measurement errors (Deaton, 2003).Selecting components of expenditure to include in the consumption aggregate can also be difficult; decisions on whether to include poorly estimated items reported in nonstandard units can have profound impacts on the consumption aggregate and the corresponding choice of poverty line.

In contrast, there are fewer factors that might cause measurement error in the weighted deprivation index. First, inputs for the weighted deprivation index do not rely on respondent recall; respondents report on their *current* asset ownership, housing status, and educational attainment. Unlike with consumption and consumption-based poverty, calculating k and MDP does not require integrating inputs that may vary by region, such as prices of goods; criteria for deprivations are standard across regions. The primary sources of error in k may derive from the data entry process or anthropometric collection of data on children under5.

In looking at cross-sectional trends, measurement error that is mean zero and independent of estimated consumption does not induce bias in the estimated poverty rate; in the aggregate, the error terms cancel each other out (Lanjouw and Lanjouw, 1997). However, measurement error is a more pertinent issue when using panel data to assess the dynamics of household consumption, income, or poverty. Generally speaking, because random measurement error in the consumption aggregate will exaggerate the magnitude of change over time for a given individual, the result will be an overestimate of the amount of movement in and out of poverty (Glewwe and Gibson, 2005). In the context of the ESS, between 2012 and 2014 this exaggeration could explain the differences observed between the magnitude of changes in *k* and MDP compared to that of changes in consumption and consumption-based poverty.

This raises the question, how much of the observed mobility in consumption can be attributed to measurement error? Glewwe (2005) performed a similar exercise using panel data from Vietnam and found that measurement error accounts for over 33 percent of measured movement in per capita expenditure and 13 percent of measured inequality. Aguero *et al.* (2007) used two waves of panel data t from South Africa to determine the proportion of observed income mobility that can be attributed to measurement error. Using health measures to instrument for wave 1 income, they found that 14 to 60 percent of movement between waves could be explained by measurement error in the income aggregate.

Regardless of the magnitude of measurement error underlying consumption mobility, it is unlikely that this error explains all the discrepancies observed between MDEP and consumption-based poverty dynamics. Consumption is arguably the easiest and quickest living standard to change; because *k* is inherently ‘stickier’, it may take households longer to accumulate enough savings to invest in multidimensional facets of wellbeing. Most likely, disparities in observed mobility between *k* and consumption can be attributed to a mix of many different factors.

5. Conclusion

MDP, as defined using the standard cut-off of k>=0.33, is a widespread burden in Ethiopia, in terms of both cross-sectional prevalence and chronic poverty over time. MDP fell only 4 pp between 2012 and 2014, from 90 to 86 percent, and at both points 82 percent of households were poor. Transitions into and out of MDP are primarily driven by changes in four deprivations (1a. At least one child aged 7-15 years in the household is not attending school.1b. No one in the household has at least six years of education. 2b. Household does not have access to an improved water source. 3d. Household does not have a radio, television, or phone, or, lacks a transportation asset, land, livestock, or refrigerator); this suggests that certain facets of wellbeing are more susceptible to change over a two-year period.

We also compare relative consumption-based poverty and MDEP, which capture the bottom 30 percent of the distributions of consumption and *k*, to assess how these two indicators interact in the cross-section and over time. Our cross-sectional analyses show that these two measures identify two very different groups as poor. In 2012, among those who were poor in either dimension, only one-third were poor in both; the same applies for 2014. This discordance needs to be considered when designing policies and programs targeting the poor – the poverty indicator selected to identify the target population can have a profound impact on who receives program benefits.

However, the minimal overlap between consumption-based poverty and MDEP in the cross-section is not entirely surprising; similar results have been found in other countries. Perhaps more interesting from a policy perspective is the lack of agreement observed between the dynamics of these two dimensions. Among individuals who experienced an improvement in their weighted deprivation index between 2012 and 2014, over half experienced a decline in their consumption. In fact, the distributions of directional changes in *k* and consumption are effectively independent; we fail to reject the null hypothesis using Pearson's chi-squared test of independence. This lack of correlation suggests that having information about an individual's change in consumption over time does not make it possible to predict change in his or her *k*, and vice versa. This finding has implications for how we assess progress in improving the wellbeing of individuals over time. Until more is learned about precisely what each of these measures is picking up, a policymaker could be missing important changes in wellbeing by focusing only on either monetary or nonmonetary measures of wellbeing or poverty. Until further evidence provides more understanding of what each indicator is capturing, both should be tracked.

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Appendix Table A: Dynamics of multidimensional equivalent poverty estimate, *k*=0.72

	Poor in Both Waves	Become Poor in Wave 2	No Longer Poor in Wave 2	Not Poor in Either Wave	Sample Size (*Households*)
Total	16.43	11.66	12.25	59.65	N=3,197
Rural	17.50	12.16	12.93	57.41	N=2,799
Small town	1.61	4.70	2.90	90.79	N=398
Amhara	22.14	11.54	15.14	51.17	N=715
Oromiya	14.17	11.63	11.28	62.92	N=636
SNNP	12.98	12.68	9.99	64.36	N=848
Tigray	16.46	8.98	11.30	63.26	N=337
All other regions	20.83	10.98	16.43	51.76	N=661

Note: Observations are weighted to make results representative of all rural and small-town individuals in Ethiopia. The *k* cutoff used to establish a multidimensional equivalent poverty estimate was determined based on the *k* value that would generate the same prevalence of poverty identified in wave 1 using annual consumption per adult equivalent.